

Quantum-Like Probabilistic Graphical Models

for Cognition and Decision

by Catarina Moreira

(Thesis Advisory Committee Report)







Motivation

Quantum physics uses **complex numbers** to represent probabilities.

Can **quantum probabilities** be used in areas outside of physics, such as **Decision-Making**?

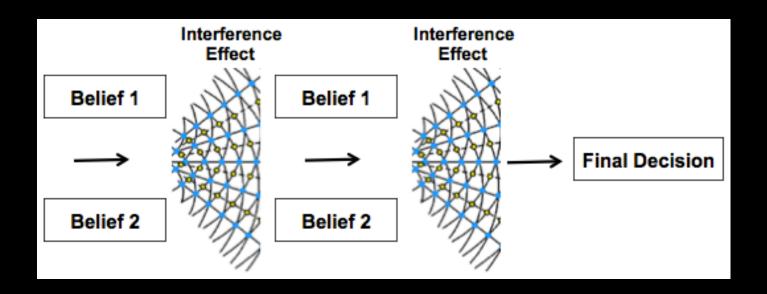
What is the **impact** of a **Decision System** that makes use of **complex numbers** to deal with **uncertainty**?

Quantum Cognition

- * Research field that aims to build **cognitive models** using the mathematical principles of **quantum mechanics**.
- * Mainly used to explain paradoxical empirical findings that violate classical laws of probability theory and logic.

Quantum Cognition

Quantum probability and interference effects play an important role in explaining several inconsistencies in decision-making.



Kolmogorov/von Neumann



Foundations of: Classical Probability (1933) Quantum Probability (1932)

Kolmogorov / von Neumann



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Quantum principles could be applied in other domains (1933-1967)
Niels Bohr

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Foundations of: Classical Probability (1933) Quantum Probability (1932) Sure Thing Principle (1954) Maurice Savage

Expected Utility Theorem (1947) von Neumann-Morgenstern



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Violations of Expected Utility (1974 – 1992)



Khaneman Tversky Shafir

Violations to the Utility Theorem (1974 – 1992)





ε-Model (1994)

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Quantum Bayesian Networks (1995)

Moreira & Wichert (2016), Quantum Probabilistic Models Revisited, Frontiers in Physics, (in press)





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Quantum Prospect Decision Theory (2010)



V. Yukalov & D. Sornett

The Quantum-Like Approach (2009)



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Quantum Bayesian Networks (1995)

Model	State representation	Quantum interference	Predictive	Comments
Quantum dynamical model	Superposition of subject's beliefs	Shröedinger's equation	No . requires manual fit	Enables time evolution
Quantum-Like approach	Contextual probabilities (observables/random variables)	Measure of supplementarity	No. requires manual fit	Can deal with hyperbolic spaces
Quantum prospect decision theory	Contextual probabilities (prospects/random variables)	Interference quarter law	Yes. Uses a static heuristic	It is predictive uses a heuristic
Quantum-Like Bayesian networks	Contextual probabilities (observables/random variables)	None	No. manual fit	Can easily scale to more complex scenarios

Research Question

Can we represent a network-based decision support system based on quantum probabilities?

Bayesian Networks

Directed acyclic graph structure in which each **node** represents a random variable and each **edge** represents a direct influence from source node to the target node.

$$Pr(B = T) = 0.001$$
 $Pr(E = T) = 0.002$ $Pr(E = F) = 0.998$

Bayesian Networks have:

- Evidence variables (observed nodes)
- Not observed nodes

ВЕ	$Pr(A=T \mid B,E)$	Pr(A=F B,E)
ТТ	0.95	0.05
ΤF	0.94	0.06
FΤ	0.29	0.71
FF	0.01	0.99

Inferences in Bayesian Networks

Inference is performed in **two** steps:

- 1. Computation of the networks full joint probability;
- 2. Computation of the marginal probability;

Full joint probability for Bayesian Networks:

$$Pr(X_1,\ldots,X_n) = \prod_{i=1}^n Pr(X_i|Parents(X_i))$$

Marginal probability for Bayesian Networks:

$$Pr_c(X|e) = \alpha Pr_c(X,e) = \alpha \left[\sum_{y \in Y} Pr_c(X,e,y) \right]$$

Where
$$\alpha = \frac{1}{\sum_{x \in X} Pr_c(X = x, e)}$$

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Bayes Assumption

Research Question

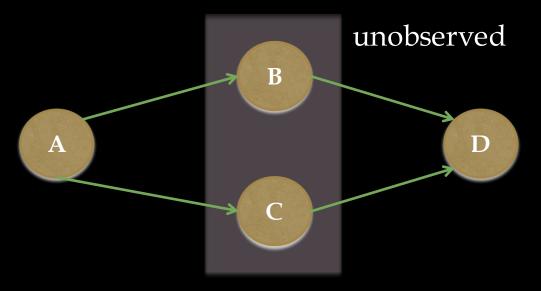
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Feynman's Path Diagram Rules

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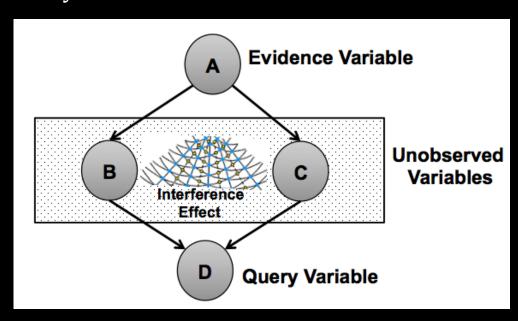


$$Pr(A \rightarrow D) = |\psi_A \cdot \psi_{B \mid A} \cdot \psi_{D \mid B} + \psi_A \cdot \psi_{C \mid A} \cdot \psi_{D \mid C}|^2 =$$

=
$$|\psi_A \cdot \psi_B|_A \cdot \psi_D|_B |^2 + |\psi_A \cdot \psi_C|_A \cdot |\psi_D|_C |^2 + Interference$$

$$Interference = 2 \cdot | \psi_A \cdot \psi_{B|A} \cdot \psi_{D|B} | \cdot | \psi_A \cdot \psi_{C|A} \cdot \psi_{D|C} | \cos(\theta_1 - \theta_2)$$

- * Under unknown events, the quantum-like Bayesian Networks can use interference effects.
- * Under known events, no interference is used, since there is no uncertainty.



* Convert classical probabilities into quantum amplitudes through Born's rule: squared magnitude quantum amplitudes.

* Classical full joint probability distribution

$$Pr(X_1,\ldots,X_n) = \prod_{i=1}^n Pr(X_i|Parents(X_i))$$

* Quantum full joint probability distribution

$$Pr_q(X_1,\ldots,X_n) = \left|\prod_{i=1}^n QPr(X_i|Parents(X_i))\right|^2$$

* Convert classical probabilities into quantum amplitudes through Born's rule: squared magnitude quantum amplitudes.

* Classical marginal probability distribution

$$Pr_c(X|e) = \alpha Pr_c(X,e) = \alpha \left[\sum_{y \in Y} Pr_c(X,e,y) \right]$$

* Quantum marginal probability distribution

$$Pr_{q}(X|e) = \gamma \left| \sum_{y} \prod_{x=1}^{N} QPr(X_{x}|Parents(X_{x}), e, y) \right|^{2}$$

- * Quantum marginal probability distribution
- * Extension of the Quantum-Like approach (Khrennikov, 2009) for N Random Variables

$$Pr_q(X|e) = \gamma \sum_{i=1}^{|Y|} \left| \prod_{x}^{N} QPr(X_x|Parents(X_x), e, y = i) \right|^2 + 2 \cdot Interference$$

$$Interference = \sum_{i=1}^{|Y|-1} \sum_{j=i+1}^{|Y|} \left| \prod_{x}^{N} QPr(X_x | Parents(X_x), e, y = i) \right| \left| \prod_{x}^{N} QPr(X_x | Parents(X_x), e, y = j) \right| \cos(\theta_i - \theta_j)$$

- * Quantum marginal probability distribution
- * Extension of the Quantum-Like approach (Khrennikov, 2009) for N Random Variables

CLASSICAL PROBABILITY

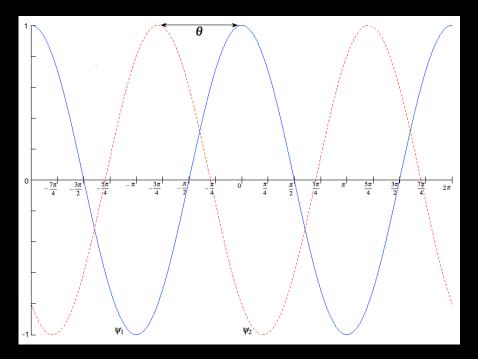
$$Pr_{q}(X|e) = \gamma \sum_{i=1}^{|Y|} \left| \prod_{x}^{N} QPr(X_{x}|Parents(X_{x}), e, y = i) \right|^{2} - 2 \cdot Interference$$

QUANTUM INTERFERENCE

$$\sum_{i=1}^{|Y|-1} \sum_{j=i+1}^{|Y|} \left| \prod_{x}^{N} QPr(X_{x}|Parents(X_{x}), e, y = i) \right| \left| \prod_{x}^{N} QPr(X_{x}|Parents(X_{x}), e, y = j) \right| \cos(\theta_{i} - \theta_{j})$$

Quantum Parameters

In Quantum Mechanics, the quantum parameter θ represents the shift of energy waves.



Quantum Parameters

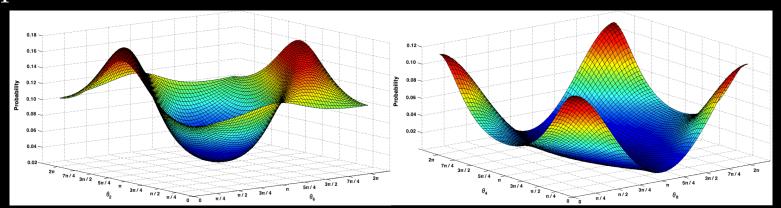
In Quantum Cognition, the quantum parameter θ represents the inner product between two random variables

Problem: Quantum Parameters

The number of parameters grows exponentially large!

$$Interference = \sum_{i=1}^{|Y|-1} \sum_{j=i+1}^{|Y|} \left| \prod_{x}^{N} QPr(X_{x} | Parents(X_{x}), e, y = i) \right| \cdot \left| \prod_{x}^{N} QPr(X_{x} | Parents(X_{x}), e, y = j) \right| \cdot \cos(\theta_{i} - \theta_{j})$$

* The final probabilities can be **ANYTHING** in some range of probabilities!



Moreira & Wichert (2016), Quantum-Like Bayesian Networks for Modelling Decision Making, Frontiers in Psychology: Cognition, 7, 1-20

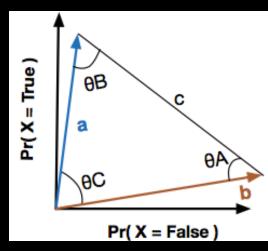
* The interference term is given as a sum of pairs of random variables.

$$interference = 2 \cdot \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} |\psi_i| \cdot |\psi_j| \cdot \cos{(heta_i - heta_j)}$$

* Heuristic: parameters are calculated by computing different vector representations for each pair of random variables.

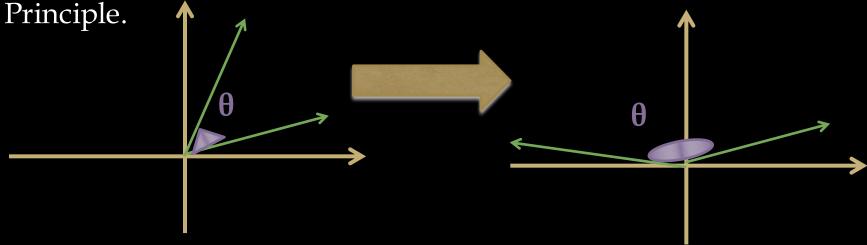
$$Pr(B) = \alpha \left[\sum_{i=1}^{N} |\psi_i|^2 + 2 \cdot |\psi_1| \cdot |\psi_2| \cdot \cos(\theta_1 - \theta_2) + 2 \cdot |\psi_1| \cdot |\psi_3| \cdot \cos(\theta_1 - \theta_3) + 2 \cdot |\psi_2| \cdot |\psi_3| \cdot \cos(\theta_2 - \theta_3) \right]$$

- * What do Bayesian Networks represent?
 - * Correlations / Causal Relationships
- * What is similarity?
 - Real-valued function that quantifies the degree of similarity between two vectors.
- * What do vectors represent?
 - * Relations between Random Variables
 - * Semantical information
- * How do we measure similarity?
 - Cosine Similarity
 - * Combining different sources of information



The vector representation of the random variables will always be positive.

We need to separate these vectors in order to obtain an interference term that can explain violations to the Sure Thing



Configuration extracted From Random Variables

Desired Configuration For Predictions

- * Vectors that are very close to each other are separated by setting their inner angle to π (minimum cosine value).
- * When vectors are already separated, we just penalize a little the angle that they share.

$$h(a, b) = \begin{cases} \pi & \text{if } \phi < 0\\ \pi - \theta_C/2 & \text{if } \phi > 0.2\\ \pi - \theta_C & \text{otherwise} \end{cases}$$

$$\phi = rac{ heta_C}{ heta_A} - rac{ heta_B}{ heta_A}$$

Validation

We validated the proposed Quantum-Like Bayesian Network and heuristic in several experiments that show **violations** to the **Sure Thing Principle**:

- the Prisoner's Dilemma Game;
- the Two Stage Gambling Game;

The Prisoner's Dilemma Game

Two players who are in separate rooms with no means of speaking to the other. Each player is offered an agreement: they have the opportunity either to betray the other (**Defect**) or to **Cooperate** with the other by remaining silent.

•

Three conditions were verified:

- Player was informed that the other chose to Defect;
- Player was informed that the other chose to Cooperate;
- Player was not informed of the other player's actions;

The Prisoner's Dilemma Game

Several experiments in the literature show violations of the Sure Thing Principle under the Prisoner's Dilemma Game.

Literature	Known to Defect	Known to Collaborate	Unknown	Classical probability
Shafir and Tversky, 1992	0.9700	0.8400	0.6300	0.9050
Croson, 1999 ^a	0.6700	0.3200	0.3000	0.4950
Li and Taplin, 2002b	0.8200	0.7700	0.7200	0.7950
Busemeyer et al., 2006a	0.9100	0.8400	0.6600	0.8750
Hristova and Grinberg, 2008	0.9700	0.9300	0.8800	0.9500
Average	0.8700	0.7400	0.6400	0.8050

$$Pr(P_2 = Defect \mid P_1 = Defect) \ge Pr(P_2 = Defect) \ge Pr(P_2 = Defect \mid P_1 = Cooperate)$$

We applied the proposed heuristic and tried to predict the probability of the player choosing to *Defect* under the Prisoner's Dilemma Game.

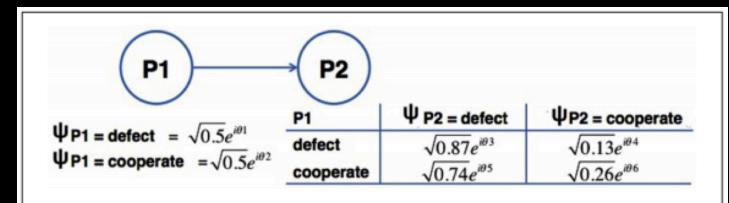
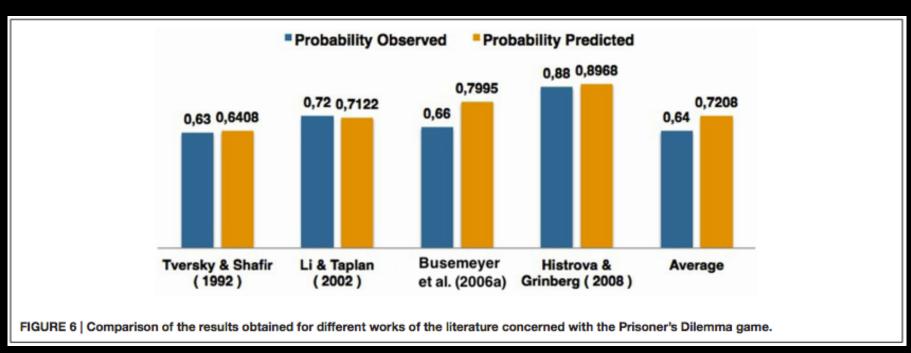


FIGURE 4 | Bayesian Network representation of the Average of the results reported in the literature. The random variables, which were considered, are P1 and P2, corresponding to the actions chosen by the first participant and second participant, respectively.

We also applied the proposed model to predict the results obtained for the Prisoner's Dilemma game for several works in the literature.

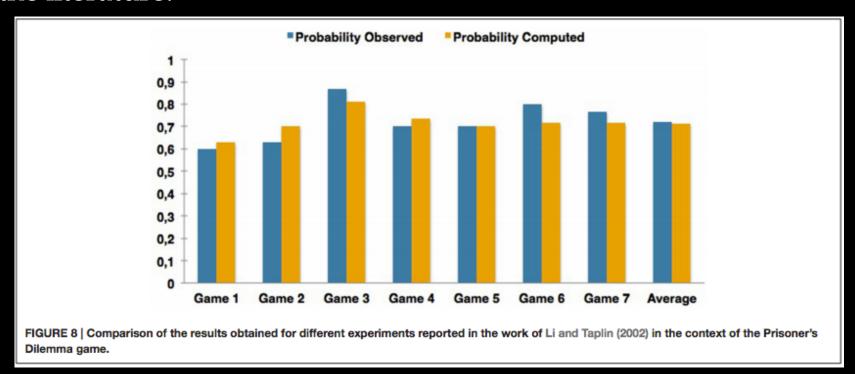


* We also applied the proposed model to predict the results obtained for the Prisoner's Dilemma game for several works in the literature.

Overall error percentage: 5.11 %

FIGURE 6 | Comparison of the results obtained for different works of the literature concerned with the Prisoner's Dilemma game.

We also applied the proposed model to predict the results obtained for the Prisoner's Dilemma game for several works in the literature.



* We applied the proposed model to predict the results obtained for the Prisoner's Dilemma game for several works in the literature.

Overall error percentage: 5.74%

FIGURE 8 | Comparison of the results obtained for different experiments reported in the work of Li and Taplin (2002) in the context of the Prisoner's Dilemma game.

The Two Stage Gambling

Participants were asked to **play a gambling game** that has an equal chance of **winning** \$200 or **losing** \$100. **Three** conditions were verified:

- **Informed** that they **won** the 1st gamble;
- Informed that they lost the 1st gamble;
- Did not know if they won or lost the 1st gamble;

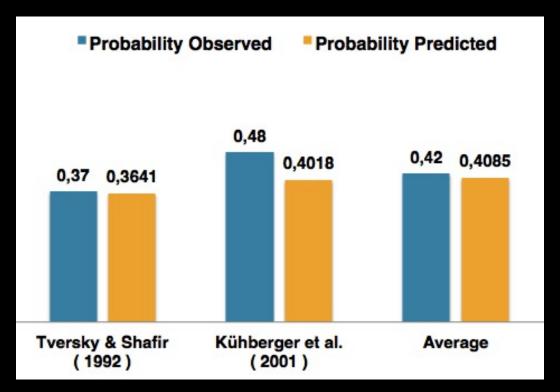
The Two Stage Gambling

* Several experiments in the literature show violations of the Sure Thing Principle under the Two Stage Gambling game.

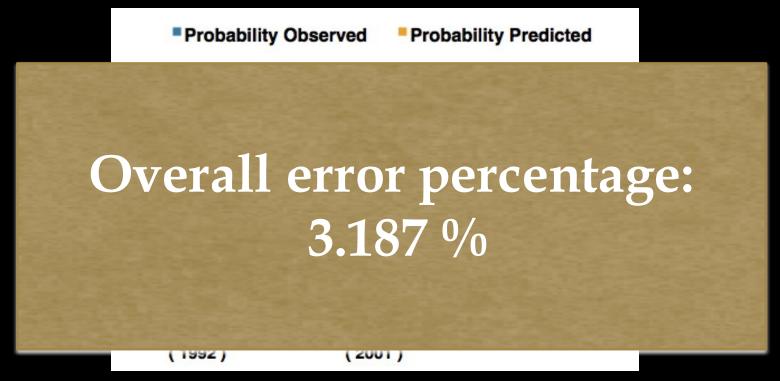
Literature	Known to Win	Known to Loose	Unknown	Classical Probability
Tversky and Shafir (1992)	0.69	0.58	0.37	0.6350
Kuhberger et al. (2001)	0.72	0.47	0.48	0.5950
Lambdin and Burdsal (2007)	0.63	0.45	0.41	0.5400
Average	0.68	0.50	0.42	0.5900

Table 7: Experimental results of the Two-Stage Gambling game reported in different works of the literature.

* We applied the proposed heuristic and tried to predict the probability of the player choosing to *play* the 2nd gamble.



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Conclusions

- * Literature overview and comparison of the different models proposed in the literature;
- * Applied the mathematical formalisms of quantum theory and Feynman's Path Diagrams to develop a Quantum-Like Bayesian Network;
- Developed an heuristic based on vector similarities in order to automatically tune quantum parameters;
- The proposed heuristic managed to make predictions for several experiments of the literature;

List of Publications

* Journal Publications:

- Catarina Moreira and Andreas Wichert, Interference Effects in Quantum Belief Networks, Journal of Applied Soft Computing, 25, 64-85, 2014
- 2. Catarina Moreira and Andreas Wichert, The Synchronicity Principle Under Quantum Probabilistic Inferences, NeuroQuantology, 13,111-133, 2015
- 3. **Catarina Moreira** and Andreas Wichert, **Quantum-Like Bayesian Networks for Modeling Decision Making**, Frontiers in Psychology: Cognition, 7, 2016
- 4. Catarina Moreira and Andreas Wichert, Quantum Probabilistic Models Revisited: the Case of Disjunction Effects in Cognition, Frontiers in Physics: Interdisciplinary Physics, in press, 2016.

List of Publications

* Conference Publications:

- 1. Catarina Moreira and Andreas Wichert, Application of Quantum-Like Bayesian Networks in Social Sciences, In Proceedings of the 4th Champalimaud NeuroScience Symposium, Champalimaud Center of the Unknown, 2015 (poster presentation)
- 2. Catarina Moreira and Andreas Wichert, The Relation Between Acausality and Interference in Quantum-Like Bayesian Networks, In Proceedings of the 9th International Conference on Quantum Interactions, 2015
- 3. Catarina Moreira and Andreas Wichert, Quantum-Like Bayesian Networks using Feynman's Path Diagram Rules, In Proceedings of the 16th Växjö Conference on Quantum Theory: from Foundations to Technologies, 2015 (extended abstract)
- 4. Catarina Moreira and Andreas Wichert, When to use Quantum Probabilities in Quantum Cognition: a Discussion, In Proceedings of the 13h Biennual Meeting of the International Quantum Structure Association, 2016 (extended abstract)